On the Negative Relationship between Labor Income Uncertainty and Homeownership: Risk Aversion vs. Credit Constraints

Luis Diaz-Serrano[♣]

National University of Ireland, Maynooth

IZA Bonn, CREB Barcelona

Abstract:

In this paper we test for the first time whether the driving force behind the negative effect of income uncertainty on owner-occupancy propensities is risk aversion or credit constraints. To disentangle this puzzle we estimate reduced form equations using Italian data. Consistent with the previous empirical evidence in the US, our results confirm that in Italy both labor income uncertainty and credit constraints exert a significant negative effect on the probability of homeownership. However, our main findings indicate that the negative relationship between labor income uncertainty and homeownership is driven by households' risk aversion.

Keywords: Homeownership, income uncertainty, credit constraints, Risk aversion

JEL classification: D1, R0, J0

[♣] National University of Ireland, Maynooth, Department of Economics (Rhetoric House), Co. Kildare, Ireland. E-mail: luis.diaz@may.ie Tel: 353-1-7083793 | Fax: 353-1-7083934.

1. Introduction

Undoubtedly owning one's dwelling is not only a signal of personal success but also one of the most important ways of wealth accumulation. Hence, barriers to homeownership have traditionally been an important research and policy issue. Historically, in most of the developed economies there has been a wide range of public policies implemented so as to promote homeownership. These range from important tax deductions and generous subsidies for the less favored homebuyers to the public provision of affordable dwellings aimed to low-income households. However, the success of these policies is condition by scarce public resources and excess demand from the less favored population groups. Hence, affordable lending has also been a main focus in the mortgage markets in most of the developed economies.

During the 1990s the mortgage industry has devoted a great effort to design mortgage products to facilitate the access to homeownership. These range from important innovations in affordable mortgage lending that reduces down payments to a minimum amount to mortgage payment protection insurance policies. The latter are specially aimed at mitigating the devastating effect that income uncertainty exerts on the homeownership propensities, though after with limited success (see e.g. Pryce and Keoghan, 2002, and Ford and Quilgars, 2001, in the UK, and Ross and Tootell, 2004, in the US). Given the lack of liquidity of home purchases and that financing the purchase of one's dwelling entails undertaking a long lasting high level of indebtedness, income uncertainty becomes itself as important as the level of income when deciding the tenure status.

Previous empirical literature on this issue observes an unequivocal negative effect of income uncertainty on the probability of homeownership. According to theoretical models, income uncertainty is expected to exert an effect on the tenure decisions after considering risk aversion, however, this assumption has never been empirically tested. In this paper we test for the first time whether the driving force behind the negative relationship between homeownership and income uncertainty is households' aversion to the risk of a mortgage default or on the contrary it is driven by credit constraints.

The relevance of carrying out such a test comes from the plausible conjecture that households with more volatile incomes might be also more credit constrained than household with steadier incomes. Disentangling this puzzle is critical in order to design public policies, improve affordability of lending, and develop more effective mortgage insurance policies aimed at promoting homeownership among those households most at income risk.

The remainder of the paper is structured as follows. In section 2 we review the literature analyzing the effect of income uncertainty and credit constraints on homeownership. Section 3 describes the data set and the empirical framework. Section 4 presents the empirical results, and section 5 summarizes and concludes.

2. Overview of the literature

During the past decade the effects of income uncertainty on homeownership have received considerable attention by economists. However, theoretical models incorporating this effect systematically tend to provide ambiguous predictions;

income uncertainty is expected to exert a negative or non-negative effect depending on differences in the construction and the assumptions underlying each model.

De Salvo and Eeckhoudt (1982) predicted a negative relationship between housing consumption and the probability of unemployment. Using a similar framework Turnbull et al. (1991) found that the relationship between income uncertainty and homeownership is generally negative, however, it might be non-negative if the expected labor income entails compensating wage differentials for income risk. Fu (1995) analyzes the demand for housing under the presence of liquidity constraints. He shows that with increasing liquidity and high risk-aversion housing investment might fall with increasing income uncertainty, however, with constant risk-aversion and if investors do not increase liquidity this result could switch to a positive effect.

Despite the ambiguity shown by theoretical models, there are some studies that explicitly test the effect of income uncertainty on the homeownership propensities and found an unequivocal negative effect. Haurin and Gill (1987), Haurin (1991) and Robst et al. (1999) report evidence based on US data, and Diaz-Serrano (2004) does for Spain and Germany.

There is also an ample range of studies in the US analyzing the effect of credit constraints on homeownership. This literature starts with Linneman and Wachter (1989) who, using criteria based on mortgage requirements that set industry standards, built indicators reflecting the degree of household’s income and wealth constraints relative to home purchases. They observed a negative effect of credit constraints on the probability of homeownership.

Using a similar framework Haurin et al. (1997) observed that the home tenure choices among young American households are also quite sensible to credit constraints. Rosenthal (2002) proxy household's credit constraints using direct responses to questions aimed at ascertaining whether the household had had any request for credit turned down or just partially granted. He also observed a lesser propensity for homeownership among credit constrained households.

Quercia et al. (2003) assessed the impact of affordable lending initiatives on homeownership rates. They observed a positive effect on homeownership but also noted that after controlling for borrowing constraints the impact is not the same across the less favored population groups. Barakova et al. (2003) studied the evolution of the effect borrowing constraints during the 1990's. They conclude that wealth constraints have a larger negative effect than income constraints on homeownership, but also that this effect is decreasing over the last decade.

Linneman et al. (1997) updated Linneman and Wachter and constructed a simulation model to measure the effect of policy changes governing constraints and mortgage interest rates on the aggregated rates of homeownership in the US. They also find wealth constraints to have a larger impact than income constraints. Bourassa (1995) is one of the few studies providing empirical evidence outside the US. He replicated Linneman and Wachter using Australian data and observed a negative effect of credit constraint on the homeownership propensities.

3. Data, variables and empirical framework

3.1. Data

The data we use in our study comes from the Italian Survey of Household

Income and Wealth (SHIW). It is a panel survey (annual from 1977 to 1987 and biannual from 1989 to 2000) carried out by *Banca d'Italia* (Central Bank of Italy). The survey contains detailed information on household characteristics, employment, income, assets, financial habits, the type of home tenure and several questions regarding the homeownership and the borrowing conditions. Additionally, starting from 1995, the survey also includes rotatory questions addressed to the study of specific issues. For our purposes, the 1995 and 2000 waves contain questions addressed to the household heads that allow us to construct a measure of individual risk aversion. We use the panel from 1986 to 2000 to estimate income uncertainty and the waves corresponding to 1995, 1998 and 2000 to evaluate credit quality constraints and to examine the determinants of the homeownership propensities.

3.2. Owning/renting user costs

Owning and renting costs is a relevant variable when analyzing the housing tenure choices. In this paper this variable is used in the estimation of the probability of homeownership, but also to perform linear regressions on preferred housing values across Italian households. We define the cost of owning relative to renting as

$$RC_k = \frac{V_k}{R_k}\left[r + p + m - t(r + p)\right], \tag{1}$$

where V_k and R_k are the deflated average house values and annual rents in region k, respectively, r is the nominal mortgage rate, p is the property tax rate, m is the maintenance rate, and t is the marginal tax rate. In equation (1) the numerator specifically refers to the owner occupancy opportunity cost (Henderson and Ioannides, 1987). The cost of owning relative to renting is computed for each of the 20 regions available in our data[1]. Deflated average house values for recent purchases, average annual rents, and average nominal mortgage interest rates are directly taken from our data set. In Italy, the property tax rate ranges from 3 percent for first time homebuyers to 7 percent, and the marginal tax rate is 19 percent up to the maximum amount of 3,615€. We use these values to estimate owning costs in equation (1). Following Robst et al. (1999) we assume a maintenance rate of 1.5 percent.

3.3. Measuring borrowing constraints

To measure to what extent a household is credit constrained we follow Linneman and Wachter (1989). Using their notation, the threshold house value that household i should aim in order not being income constrained (V^I) and wealth constrained (V^W) is:

$$V_i^I = 0.35\frac{I_i}{r}, \quad V_i^W = 5 \cdot W_i \ , \tag{2}$$

[1] These regions are Piemonte, Valle d'Aosta, Lombardia, Trentino, Veneto, Friuli, Liguria, Emilia Romagna, Toscana, Umbria, Marche, Lazio, Abruzzi, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna.

where r is the mortgage interest rate, I is the annual household income, and W is the net household wealth. Since house values are only observed for homeowners, we use a subsample of unconstrained homeowners, those with observed house value lower 85 percent of both V^I and V^W, to estimate the following housing demand equation

$$V_i^* = X_i \beta + u_i, \tag{3}$$

where V^* is the preferred house value, X is a vector of household characteristics which also includes house preferences, β is a parameter vector to be estimated, and u_i is a random error term. In a second stage we use $\hat{\beta}$ to impute a $\hat{V}_i^*$ to each household either homeowner or renter. Hence, we assume that a household is income constrained (*IC*) or wealth constrained (*WC*) if $\hat{V}_i^* > 0.9 \cdot V_i^I$ or $\hat{V}_i^* > 0.9 \cdot V_i^W$, respectively.

Equation (3) is estimated using a pooled sample covering the waves 1995, 1998 and 2000. Since using pooled data may lead to inefficient estimates we just select the last wave the household has participated. The explanatory variables (X) in equation (3) are a set of variables regarding the household, i.e. a squared polynomial on household income and the number of children; some characteristics of the household head, i.e. a squared polynomial on age, marital status and gender; a set of geographical dummies, i.e. region and city size; the costs of owning relative to renting and year dummies.

The linear estimation by OLS of the preferred housing value equation (3) is reported in table 1. Most of the variables considered are significant at 1 percent or better. Both the household income and the age of the household head show a positive but decreasing effect. Higher preferred house values are observed in the North-East of Italy and the Islands, and it is decreasing with the city size.

Insert table 1 around here

Additionally, our dataset also provides some questions that allow us directly measure borrowing constraints in the same way as in Rosenthal (2002). These questions are:

C54. *During the last 12 months did your household apply to a bank or a financial company for a loan or a mortgage?*

C55. *Was the application granted in full, in part or rejected?*

C56. *During the last 12 months did you or another member of your household consider the possibility of applying to a bank or a financial company for a loan or a mortgage but then change his/her mind thinking that the application would be rejected?*

From answers to C54-C56 we create a dummy variable that takes 1 if the loan was denied, just partly granted, or if any member refrained from applying concerned of being turned down. We call this direct proxy of being credit constrained *DCC*. Additionally to *IC* and *WC* we also use *DCC* to examine the effect of credit constraints on the probability of homeownership. Table 2 shows a summary statistics on *IC*, *WC* and *DCC*. As expected we observe that renters tend to be more credit constrained than homeowners.

Insert table 2 around here

3.4. Measuring income uncertainty

Following Robst et al. (1999) income uncertainty is measured using the household head's net annual labor income. Although housing purchases are mostly planned taking into account household's income, there are several reasons to sustain that household head labor income would be more important than other sources of income in the housing tenure decisions[2]. Firstly, it is the main component of the household's net disposable income. And secondly, it also tends to be steadier than other sources of income as e.g. wife's income. Of course, it does not implies that wife's income is not relevant, but variations in wife's income has more to do with entries and exits in the labor market due to fertility, and tied-mobility linked to their husbands. Therefore, income volatility for most married woman has less to do with income risk coming from market forces.

In Italy, in 1986 the share of the household head labor income in the overall household income was 70 percent and in 2000 this share was 60 percent. Hence, because of its more transitory nature, the remaining share of the household income composed by other members' wages, assets or public subsidies are not considered when computing income uncertainty. Additionally, since our measure of risk-

[2] See Robst et al. (1999) for a more extensive discussion.

aversion can be computed only for the household heads it is convenient estimating labor income uncertainty just using the household head labor income.

To proxy labor income uncertainty we turn to the decomposition of income into a permanent and a transitory component. Variables affecting permanent labor income such as experience, education, gender or region are expected to generate systematic variations in income. These variations in permanent labor income are foreseeable by individuals, therefore, a suitable measure of income uncertainty should be purged of these systematic variations that have nothing to do with risk. We estimate a panel data regression on household head labor income as follows[3]

$$\ln(w_{it}) = Z_{it}\gamma + \alpha_i + e_{it}\,, \tag{4}$$

where the subscripts i and t indexes households and time, respectively; $\ln(w_{it})$ is the natural logarithm of the household head net annual labor income; Z_{it} is a set of explanatory variables referring to the household head; α_i is an intrinsic individual time-constant shock in earnings, which is normally distributed; e_{it} is a time-varying white-noise random shock in earnings; and γ is the set of parameters to be estimated. We estimate equation (4) using a panel data model with random effects (Hsiao,1986, Ch. 4) using the panel covering the period 1986-2000. The explanatory variables (Z) in equation (4) are years of schooling, a squared

[3] Typically, transitory income and permanent income add up to equal total income. This property calls for a linear-linear specification of the labor income equation. However, since the log-linear specification provides a remarkably better fit, following Robst *et al.* (1999) we also chose the log-linear specification.

polynomial on potential years of work experience, gender and a set of regional and city size dummies.

One advantage of the labor income equation (4) is that it estimates the systematic component (α_i) due to unobserved factors such as ability, effort, etc. Hence, transitory shocks in labor income (e_{it}) can be netted out from this systematic component. Income uncertainty will be estimated using the time-varying component of the estimated residuals in equation (4) as follows:

$$\hat{\sigma}_{ei}^2 = \frac{1}{T}\sum_{t=1}^{T}\left\{\hat{\eta}_{it} - \overline{\eta}_i\right\}^2 , \tag{5}$$

where $\hat{\eta}_{it} = \exp(\hat{e}_{it})$, $\overline{\eta}_i$ is the average over time of $\hat{\eta}_{it}$ for each household and the exponential transformation is used in order to transfer back $\hat{e}_{it}$ to the money metric[4].

Table 1 shows the estimation of the labor income equation (4). All the explanatory variables are highly significant and have the expected signs. Table 3 reports the level of income uncertainty for selected population groups. As expected, renters face, on average, about 42% more uncertainty than owners, 0.37 vs. 0.26, respectively. Labor income uncertainty is decreasing with age up to 50 years old for owners and increasing for renters. In wealthier regions (North), income uncertainty is markedly lower than in the poorer (South and Islands). In these

[4] By definition we have $\frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T} e_{it} = 0$. However, since our measure of transitory income is just the average over time for each household we get that $\overline{e}_i = \frac{1}{T}\sum_{t=1}^{T} e_{it} \neq 0, \quad \forall i$.

regions the gap in income uncertainty between owners and renters is also larger. Moreover, for the rest of the household head characteristics the levels of income uncertainty display a reverse pattern between owner and renters. These results suggest that tenure choices might be strongly influenced by this variable.

Table 3 around here

3.5. Measuring risk aversion

Our measure of risk-aversion is based on individual responses to the following question:

"*You are offered the opportunity of acquiring a security permitting you, with the same probability, either to gain 10 million lire* (≅ €5,200) *or to lose all the capital invested. What is the most you are prepared to pay for this security?*"

Using a Taylor series approximation to the utility function Hartog et al. (2002) obtain the following approximate expression for the Arrow-Pratt measure of absolute risk aversion (ARA):

$$ARA_i = \frac{(\lambda Z - P_i)}{\left[\frac{1}{2}(P_i^2 + \lambda Z^2) - \lambda P_i Z\right]}, \qquad (6)$$

where λ is the probability of wining this "lottery", Z is the "prize" and P is the amount that individuals are willing to pay. According to expression (6) individuals who are willing to pay about 5 million lire (P≅€2,600) are assumed to be risk neutral (ARA=0), bellow this amount individuals are assumed to be risk averse (ARA>0), and above this amount risk lovers (ARA<0). For maximum risk aversion (P=€0) we get ARA=2/Z, and for maximum risk loving (P≅€5,200) we get ARA=-2/Z.

In total 8,135 household heads answered this question in 1995 and 3,933 did so in 2000. This corresponds to 12,068 individuals, from who 950 participated in both waves. We show a summary statistics in table 4. The distribution of individual risk aversion in our sample report a similar distribution to that observed in Guiso and Paiella (2001) for Italy, and in Hartog *et al.* (2002) for The Netherlands, though Dutch tend to be more risk-averse than Italians. We find that in 1995 about 76.5 percent of the respondents were risk-averse, about 17 percent were risk-neutral and about 6.5 percent were risk-lovers. However, in 2000 risk-aversion rose up to 92.4 percent, and risk neutrality and risk loving felt up to 6.7 and 0.85 percent, respectively.

Table 4 around here

Measuring risk aversion based on hypothetical lottery games is often criticized. Some researchers doubt about whether such questions can be answered in a meaningful way, and whether the answers can really be correlated with real risk undertaking propensities (e.g. risk taken in portfolio investments). To deal with this criticism, we test the performance of our risk aversion measure (*ARA*) with two individual decisions that are assumed to be strongly dependent on the degree of risk aversion. These are self-employment and investment in risky assets (bonds, shares and mutual funds overall household's portfolio). Results are presented in table 5.

Table 5 around here

We use three different models to validate our *ARA* measure with the investment in risky assets. Firstly, a probit model where the endogenous variable is a dummy variable that takes 1 if the household holds risky assets in the portfolio. Secondly, a generalized linear model where the endogenous variable is the percentage of risky assets in the overall portfolio. And thirdly, a Tobit model on the total amount invested in risky assets with truncation at zero. In the case of self-employment we use a single probit specification. In all cases our measure of risk aversion shows a negative and highly significant effect (at 1 percent or better).

3.6. Econometric model

The observed endogenous variable in our econometric model, y_i, is binary, taking the value one if the household i is homeowner and 0 otherwise. In this context, y_i, is the realization of the unobserved propensity for homeownership for each household, y^*_i. Hence, the econometric specification can be written as

$$y_i = I(y_i^* > 0) = I(H_i^{'}\delta + \nu_i > 0) \qquad (i = 1, ..., N), \tag{7}$$

where $I(\bullet)$ is a binary indicator function that takes one if the argument is true and zero otherwise, H_i is a vector of explanatory variables, δ is the vector of coefficients to be estimated, and ν_i is the error term. If we expand equation (7) to consider the effect of both credit constraints (*CC*) and labor income uncertainty ($\sigma^2_{\varepsilon i}$) as measured in expression (5) we have

$$y_i = I(y_i^* > 0) = I(H_i^{'}\delta + CC_i\lambda + \hat{\sigma}^2_{\varepsilon i}\pi + \nu_i > 0) \qquad (i = 1,\ldots,N)\,, \tag{8}$$

From equation (8) we should expect λ<0 (e.g., Linneman and Wachter, 1989, Bourassa, 1995, Haurin et al., 1997, Rosenthal, 2002, and Barakova et al., 2003), and π<0 (Haurin, 1991, Robst et al., 1999, and Diaz-Serrano, 2004a). Estimates of the parameters in equation (8) coming from a single univariate probit model will be, however, inconsistent if ν_i and the error term of a potential binary equation where CC_i is the endogenous variable are correlated (see Woolbridge 2002, p. 477). In this context, the bivariate probit model would provide consistent estimates.

As mentioned earlier, the main focus of the paper aims to test whether the effect of labor income uncertainty ($\sigma^2_{\varepsilon i}$) is driven by household's risk-aversion (to e.g. a mortgage default) or on the contrary it is driven by household's credit constraints (e.g. no access to the mortgage market). This test requires estimating equation (8) for different population groups; credit vs. non-credit constrained, and risk vs. non-risk averse. The size and the significance of the estimated effects for π in equation (8) for each of these population groups will allow us disentangling the puzzle. As in Rosenthal (2002), the model consists of two equations and can be expressed as follows

$$y_{1i} = I(y_{1i}^{*} > 0) = I(H_{1i}^{'}\delta_1 + \nu_{1i} > 0) \qquad (i = 1,...,N)$$
$$y_{2i} = I(y_{2i}^{*} > 0) = I(H_{2i}^{'}\delta_2 + \hat{\sigma}_{\varepsilon i}^{2}\pi_2 + \nu_{2i} > 0) \qquad (i = 1,...,N) \tag{9}$$

where $y_{i1}{}^{*}$ is the latent variable indicating the propensity to be or not credit constrained, or risk or non-risk averse, and $y_{i2}{}^{*}$ is the latent indicator regarding the propensity for homeownership, where $(\nu_{1i}, \nu_{2i}) \sim BVN(0,0,1,1,\rho)$. The matrixes H_{1i} and H_{2i} do not need to contain the same variables. The explanatory variables in the tenure choice equations (8) and (9) are a set of household head's characteristics, i.e education, a squared polynomial on age, marital status, and self-employment; a set of household's variables, i.e. size, number of dependent members (no income recipients), household income; a set of dummies collecting the credit situation (outstanding bank debts); a set of geographical dummies, i.e. regional dummies, city size and household's location; and as our key variables we include labor income uncertainty and a set of dummies regarding credit constraints. However, since in the system of equations (9) the tenure choice equation is specifically estimated for credit or non-credit constraint households, dummies referring to credit constraints are dropped from this equation.

In the system of equations (9) we face both a censoring and observation rule for both y_{i1} and y_{i2}, which lead us to consider the sample selection issue. Hence, we need to control for correlation between the error terms and the sequence of "choices". For each tenure outcome we have three types of observation: being (non-)credit constrained; being homeowner; and not being homeowner. Analogously, we can draw the same sequence in the case that the first latent indicator (y_{i1}^{*}) refers to the propensity of being or not risk averse. The unconditional probabilities of this binary tree are given by:

$$
\begin{aligned}
&P(y_{i1}=1 \cap y_{i2}=1)=\Phi_2(H_{i1}\delta_1, H_{i2}\delta_2, \rho)\\
&P(y_{i1}=1 \cap y_{i2}=0)=\Phi_2(H_{i1}\delta_1, -H_{i2}\delta_2, -\rho)\\
&P(y_{i1}=0)=1-\Phi(H_{i1}\delta_1)
\end{aligned}
\tag{10}
$$

where Φ and Φ_2 denote the univariate and bivariate standard normal cumulative distribution functions, respectively. And, the resulting log-likelihood function is given by

$$
\begin{aligned}
LogL = &\sum_{\substack{y_{1i}=1\\ y_{2i}=1}} \log \Phi_2(H_{i1}\delta_1, H_{i2}\delta_2, \rho) + \\
&+\sum_{\substack{y_{1i}=1\\ y_{2i}=0}} \log \Phi_2(H_{i1}\delta_1, -H_{i2}\delta_2, -\rho) + \sum_{y_{1i}=0} \log\left(1-\Phi(H_{i1}\delta_1)\right),
\end{aligned}
\tag{11}
$$

Finally, to estimate the models (8) and (9) we restrict our sample to homeowners having outstanding mortgage payments and that purchased their dwelling after 1989. By applying the former restrictions we keep out of the sample households that have purchased their dwelling too long ago, have not needed a mortgage or have inherited the dwelling. Obviously, these households might never experience a mortgage default, therefore, they are not expected to follow the same choice rules that homeowners that are currently mortgage borrowers. By considering these households in the sample the true relationship between income uncertainty and the probability of homeownership might be “obscured”. Given that the necessary information to know whether a household is credit constrained or risk-averse is only available from 1995, to estimate our econometric model we pool the corresponding cross-sections for 1995, 1998 and 2000. In order to avoid inefficiency we just take the last wave the household has participated.

4. Econometric results

Table 6 and 7 report the econometric estimation of the probability of homeownership. Table 6 focuses on the univariate and bivariate probit estimates to evaluate the effect of labor income uncertainty and credit constraints on the probability of homeownership (equation 8). Recall that given the nonlinear nature of the univariate and bivariate probit models, the estimated coefficients lack any economic interpretation and are just used to determine the sign of the relationship. However, at this stage this is just what we are interested in.

The credit constraint equation in the bivariate probit model is included to avoid the inconsistency of the parameters in the homeownership equation. It is worth noting that correlation between both equations turns out to be highly significant ($\rho \neq 0$), which means that controlling for this correlation is critical. Households with older household heads and with more dependent members have higher propensity to be credit constrained. Household income, education of the household head and his/her self-employment status exerts a negative effect on such a propensity. This equation also includes a set of dummy variables collecting the effect of the outstanding bank debts for the purchase of different goods. We find this set of variables to be more important on wealth constraints than on income constraints.

Our main findings concern the owner-occupancy equation. Consider first the role of the credit constraints. Consistent with the previous evidence, we find that in Italy both wealth constraints (*WC*) and income constraints (*IC*) exert a significant and negative effect on the probability of homeownership, though with a remarkably larger effect of the wealth constraints. The former result coincides with what was observed in the US[5]. Note that our proxy of credit constraints (*DCC*) based on direct questions shows also a significant and negative effect. The estimates coming from the bivariate probit model also confirm that the credit constraint parameters in the homeownership equation are quite sensible to the omission of the endogenous nature of the household's credit constraints propensities. We find a significant downwards bias in the credit constraints parameters coming from the univariate probit model, -0.38 vs. -0.78 for income constraints (models 1 and 2, table 6) and –3.33 vs. –4.03 for wealth constraints (models 3 and 4, table 6).

Turning our attention to the effect of income uncertainty on homeownership, consistent with the previous empirical evidence for the US, Germany and Spain, we also observe a significant and negative effect in Italy. Other differences across models are observed in the effect of other variables considered in the owner-occupancy equation, but the signs persistently remain in all models. Owner-

[5] We have also carried out a number of alternative specifications. In models where income and wealth constraints are simultaneously considered, income constraints have turned out to be statistically insignificant. Therefore, the effect of wealth constraints dominates over income constraints. Alternatively, we have also estimated a trivariate probit model using the simulated maximum likelihood method that simultaneously estimates the probability of homeownership and the wealth and income constraints propensities, and once more we observe that the wealth constraints effect dominates over the income constraints effect.

occupancy is more likely in smaller cities (less than 500,000 inhabitants), and out of the city center and in isolated areas. As expected, household head age, family income and being married raise the propensity to own, whereas household size and education exert a negative effect. This counter intuitive result contrasts with the observed in Spain, but coincides with previous evidence for Germany (see Diaz-Serrano, 2004).

Insert table 6 around here

Turning to our major findings, we focus now on the estimates of the effect of income uncertainty on the probability of homeownership shown in table 7. Recall that this estimates comes from the system of equations (9). Although all models in table 7 include the same explanatory variables (except credit constraints in the homeownership equation) than the estimates reported in table 6, for the sake of simplicity we focus on the estimated parameters and effects associated to labor income uncertainty in the homeownership equation. To facilitate interpretation and the comparison between alternative models we also report the average marginal effects (APE). The single effect of labor income uncertainty in the homeownership equation can be computed as in the univariate probit as $\phi_i(H_{2i}\delta_2 + \sigma_{2i}^2\pi_2)\cdot\pi_2$, where ϕ is the standard normal density and π_2 is the parameter associated to the labor income uncertainty (Christofides et al., 1997).

We have estimated the APE for different population groups depending on whether they are or not credit constrained, and whether they are or not risk averse.

These results are crucial to determine the nature of the negative relationship between homeownership and labor income uncertainty. First at all, we shall remark that the high statistical significance of the correlation terms suggests that controlling for sample selection is critical to obtain unbiased estimates.

Differences in the APE of labor income uncertainty between credit and non-credit constrained are fairly modest, -0.067 vs. -0.078 for wealth (un)constrained, respectively, and –0.289 vs. -0.236 for income (un)constrained, respectively. Major differences in this negative relationship are reported when considering risk-averse vs. non risk-averse households, -0.319 vs. –0.041, respectively. For the risk averse, a 10 percent increase in the average labor income uncertainty decreases about -3.25% the probability of being homeowner, whereas for the non-risk averse this effect has turned out to be statistically insignificant. For income (un)constrained households these percentages are –2.95% vs. –2.41%, respectively, and –0.68% vs. –0.80% for wealth (un)constrained households. These results suggest that the negative link between income uncertainty and the homeownership propensities is driven by risk-aversion.

5. Conclusions and discussion

In this paper we have investigated the effect of labor income uncertainty and credit constraints on the probability of homeownership in Italy. Consistent with the previous empirical evidence, we find that in Italy credit constrained households and with more volatile incomes are less likely to own their dwelling. As in the US, we also observe that although both types of constraints are important, the wealth constraints effect dominates over the income constraints effect.

As the main focus of this paper we have investigated for the first time the underlying nature in the negative link between labor income uncertainty and homeownership. To carry out the test we have performed reduced form estimates using the bivariate probit model with sample selection. We observe that the gap in the estimated negative effect of income uncertainty on homeownership between credit and non-credit constrained households is immaterial. However, a markedly larger gap is found between risk and non-risk averse households, and being indeed statistically insignificant for the non-risk averse. These results indicate that the negative effect of income uncertainty on the homeownership propensities is driven by household’s risk aversion.

The corollary of our results suggests that institutions and the banking industry should devote greater efforts to promote homeownership among those households most at income risk. Probably, more efficient mortgage protection payment insurance policies should be designed in order to mitigate the devastating effect of income uncertainty on the homeownership propensities of the more risk-averse households. We find this is an important issue that still is under-researched.

References

Barakova I., R.W. Bostic, P.S. Calem, S.M. Wachter, 2003, Does credit quality matter for homeownership?, Journal of Housing Economics 12, 318-336.

Bourassa S.C., 1995, The impacts of borrowing constraints on home-ownership in Australia, Urban Studies 32, 1163-1173.

Christofides L.N., T. Stengos, R. Swidinsky, 1997, On the calculation of marginal effects in the bivariate probit model, Economics Letters 54, 203-208.

DeSalvo, J.S., L.R. Eeckhoudt, 1982, Household behavior under income uncertainty in a monocentric urban area, Journal of Urban Economics 11, 98-11.

Diaz-Serrano L., 2004, Labor income uncertainty, risk-aversion and homeownership, IZA discussion paper #1008, IZA Bonn.

Ford, J., Quilgars, D., 2001. Failing home owners? The effectiveness of public and private safety-nets. Housing Studies 16, 147-162.

Fu Y., 1995, Uncertainty, liquidity, and housing choices, Regional Science and Urban Economics 25, 223-236.

Guiso L., M. Paiella, 2001, Risk aversion, wealth and background risk, CEPR discussion paper #2728, CEPR London.

Hartog J., A. Ferrer-i-Carbonell, N. Jonker, 2002, Linking measured risk aversion to individual characteristics, Kyklos 55, 3-26.

Hartog J., E.J.S. Plug, L. Diaz-Serrano, A.J.C. Vieira, 2003, Risk compensation in wages: a replication, Empirical Economics 28, 639-647.

Haurin D.R., P.H. Hendershott, S.M. Wachter, 1997, Borrowing constraints and the tenure choice of young households, Journal of Housing Research 8, 137-154.

Haurin, D.R., H.L. Gill, 1987, Effects of income variability on the demand for owner-occupied housing, Journal of Urban Economics 22, 136-150.

Haurin, D.R., 1991, Income variability, homeownership, and housing Demand, Journal of Housing Economics 1, 60-74.

Haurin, D.R., P.H. Hendershott and D. Kim, 1994, Housing decisions of American youth, Journal of Urban Economics 35, 28-45.

Henderson, J.V. and Y.M. Ioannides, 1987, Owner occupancy: consumption vs. investment demand, Journal of Urban Economics 21, 228-241.

Hsiao, C., 1986, Analysis of panel data. (Cambridge University Press, Cambridge).

Linneman P.D. and S.M. Wachter, 1989, The impacts of borrowing constraints on homeownership, AREUEA Journal 17, 389-402.

McGoldrick K., 1995, Do women receive compensating wages for earnings uncertainty?, Southern Economics Journal 62, 210-222.

Ortalo-Magne, F., and S. Rady, 2002, Tenure choice and the riskiness of non-housing consumption, Journal of Housing Economics 11, 266-279.

Pryce, G., Keoghan, M., 2002. Unemployment insurance for mortgage borrowers: is it viable and does it cover those most in need?. European. Journal of Housing Policy 2, 87-114.

Quercia, R.G., G.W. McCarthy, and .M. Wachter, 2003, The impacts of affordable lending efforts on homeownership rates, Journal of Housing Economics 12, 29-59.

Robst, J., R. Deitz, and K. McGoldrick, 1999, Income variability, uncertainty and housing tenure choice, Regional Science and Urban Economics 29, 219-229.

Ross, S.L., Tootell, G.M.B, 2004. Redlining, the community reinvestment act, and private mortgage insurance. Journal of Urban Economics 55, 278-297.

Rosenthal S.S., 2002, Eliminating credit barriers: how far can we go?, in: Retsinas N.P., Belsky E.S., eds., Low-income homeownership, 111-145.

Turnbull, G.K., J.L. Glascock and C.F. Sirmans, 1991, Uncertain income and housing price and location choice, Journal of Regional Science 31, 417-433.

Wooldbridge, J.W., 2002, Econometric analysis of cross section and panel data (MIT Press, Cambridge).

Table 1: Estimation of the house preferred value according to equation (5), and of the labor income equation (6)

	Preferred House value (OLS)		Household head annual earnings (Panel with random effects)	
	Coefficient	t-stat	Coefficient	t-stat
Constant term	35,051.76	4.71	9.5336	616.82
Household income	1.4316	43.41		
Household income squared	$-1.1 \cdot 10^{-6}$	-17.10		
Number of children	7,154.77	7.74		
<u>Household head characteristics</u>				
Age	1,477.85	3.47		
Age squared	-9.8867	-2.55		
Married	1,924.12	0.75		
Female	-914.15	-0.41	-0.2905	-53.25
Years of schooling			0.0562	84.40
Experience			0.0150	25.98
Experience squared			-0.0002	-36.24
<u>Region (base North-West)</u>				
North-East	13,192.68	5.47	-0.0463	-6.64
Centre	4,387.64	1.79	-0.0909	-14.08
South	9,900.65	3.71	-0.1770	-27.71
Islands	12,563.72	3.23	-0.1803	-23.00
<u>City size (base <20,000)</u>				
20,000 to 40,000	-4,556.10	5.15	0.0386	5.69
40,000 to 500,000	-12,030.17	6.59	0.0748	13.12
More than 500,000	-20,683.19	3.12	0.1077	13.59
Relative cost of owning	15.1233	3.85	0.0386	5.69
Year dummies	Yes			
F-test	239			
Wald test			29,064	
ρ			0,369	
R-squared	0,461		0,364	
Sample size	4,766		59,065	

Table 2: Sample means for borrowing constraints variables

	Wealth Constrained (*WC*)			Income Constrained (*IC*)			Direct answers (*DCC*)		
	full	renter	owner	full	renter	owner	full	renter	owner
Total	0.243	0.792	0.014	0.378	0.514	0.321	0.091	0.154	0.063
Household head age									
Up to 30	0.441	0.831	0.008	0.362	0.479	0.231	0.087	0.128	0.054
31-40	0.316	0.767	0.009	0.324	0.436	0.247	0.078	0.128	0.048
41-50	0.228	0.744	0.006	0.303	0.441	0.244	0.099	0.182	0.064
51-65	0.177	0.766	0.009	0.331	0.481	0.288	0.085	0.127	0.074
more than 65	0.249	0.870	0.029	0.526	0.699	0.464	0.139	0.353	0.073
Region									
North-West	0.262	0.785	0.003	0.250	0.388	0.181	0.030	0.138	0.073
North-East	0.215	0.794	0.011	0.326	0.487	0.269	0.029	0.143	0.060
Centre	0.214	0.756	0.006	0.316	0.438	0.269	0.052	0.096	0.066
South	0.266	0.830	0.026	0.527	0.668	0.468	0.124	0.237	0.152
Islands	0.254	0.790	0.035	0.574	0.701	0.522	0.081	0.222	0.124
City size									
Up to 20,000	0.208	0.807	0.022	0.475	0.594	0.438	0.078	0.234	0.114
20,000 to 40,000	0.221	0.775	0.010	0.395	0.540	0.341	0.085	0.154	0.105
40,000 to 500,000	0.261	0.801	0.012	0.336	0.499	0.261	0.047	0.121	0.070
more than 500,000	0.298	0.762	0.004	0.258	0.403	0.165	0.048	0.169	0.101

Table 3: Sample means for labor income uncertainty

	Full sample	Renter	Owner
Total	0.264	0.373	0.263
Household head age			
Up to 30	0.398	0.416	0.327
31-40	0.258	0.290	0.249
41-50	0.230	0.348	0.228
51-65	0.292	0.422	0.290
more than 65	0.279	0.429	0.274
Household head characteristics			
Married	0.260	0.396	0.258
Not married	0.284	0.283	0.285
Self-employed	0.450	0.552	0.228
Not self-employed	0.230	0.345	0.373
Unemployed	0.326	0.461	0.230
Not unemployed	0.261	0.373	0.260
Region			
North-West	0.246	0.362	0.228
North-East	0.272	0.295	0.271
Centre	0.245	0.258	0.229
South	0.260	0.427	0.254
Islands	0.330	0.777	0.322

Table 4: Sample statistics for risk aversion

	1995		2000	
	N	%	N	%
Answered the question	5,814	71,5	3,193	81.2
Did not answer the question	2,321	28,5	740	18.8
Total respondents	8,135		3,933	
Risk Averse (P<2,600€)		76.5		92.4
Risk Neutral (P=2,600€)		16.9		6.8
Risk Lovers (P>2,600€)		6.6		0.8

Note: (1) Including all valid responses; (2) Including only positive responses.

Table 5: Performance tests for absolute risk aversion (ARA)

	Investment in risky assets						**Self-employment**	
	Probit(1)		GLM(2)		Tobit(3)		Probit(4)	
	Coeff.	z-value	Coeff.	z-value	Coeff.	t-value	Coeff.	z-value
Constant	-9.6460	-15.78	-15.7241	-14.63	-21.1653	-22.52	-3.4268	-8.77
ARA	-1.3184	-6.08	-1.5738	-4.00	-2.2792	-5.86	-0.6981	-3.52
Log(income)	0.7114	12.53	1.0825	11.94	1.6544	20.32	0.1073	3.11
Age	0.0226	2.14	0.0620	2.21	0.0325	1.69	0.0863	7.77
Age squared	-0.0002	-1.97	-0.0006	-2.14	-0.0003	-1.49	-0.0011	-9.71
Schooling	0.0687	10.37	0.0606	4.29	0.1074	8.80	-0.0019	-0.31
Female	-0.1044	-1.94	-0.2232	-1.81	-0.2821	-2.51	-0.5254	-10.32
Region dummies								
(base North-West)								
North-East	-0.0511	-0.95	-0.0840	-0.77	-0.1096	-1.11	0.1349	2.56
Centre	-0.1820	-3.15	-0.4312	-3.26	-0.3405	-3.19	0.1004	1.89
South	-0.5798	-8.49	-0.8940	-5.49	-0.9058	-6.92	0.0134	0.25
Islands	-0.6862	-6.95	-0.9293	-3.11	-1.1740	-6.16	0.0303	0.45
1995	-0.1760	-3.98	-0.5357	-5.25	-0.3538	-4.27	0.0856	2.37
Sample size					8,414			

Note: (1) Endogenous variable: Dummy takes 1 if the household has risky asset in the portfolio; (2) Endogenous variable: Percentage of investment in risky assets overall portfolio. In the generalized linear model I use a logit function on the endogenous variable; (3) Endogenous variable: Total amount invested in risky assets. Truncation point at 0; (4) Endogenous variable: Dummy takes one if the household head is self-employee.

Table 6: Estimates of the effect of labor income uncertainty and credit constraints on the probability of homeownership (univariate and bivariate probits).

	Univariate Probit (Model 1)		Bivariate Probit (Model 2)				Univariate Probit (Model 3)		Bivariate Probit (Model 4)			
	Homeownership		Homeownership		IC		Homeownership		Homeownership		WC	
	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat
Constant term	1.3253	4.61	1.6403	5.88	2.0252	12.76	3.7505	9.07	4.1114	11.33	2.2036	7.74
Age	-0.0160	-1.86	-0.0188	-2.25	0.0158	8.64	-0.0503	-3.70	-0.0481	-4.06	0.0090	6.87
Age squared	0.0001	1.11	0.0001	1.63			0.0004	3.21	0.0004	3.79		
Household size	-0.1056	-5.25	-0.1069	-5.53			-0.1015	-3.65	-0.1136	-4.61		
Married	0.2942	6.04	0.2640	5.53			0.3137	4.18	0.2572	3.79		
Dependent					0.2617	10.80					-0.0124	-0.76
Years of Schooling	0.0148	2.37	0.0087	1.47	-0.0349	-6.88	-0.0255	-3.01	-0.0340	-4.51	-0.0361	-6.02
Self-employed	0.1738	3.36	0.1939	3.77	0.0960	1.24	-0.3650	-5.55	-0.4545	-7.04	-0.4621	-7.62
Income uncertainty	**-0.5466**	**-5.55**	**-0.5239**	**-5.95**			**-0.2968**	**-2.73**	**-0.3123**	**-3.46**		
Family income	$1.2\cdot10^{-5}$	7.04	$9.3\cdot10^{-6}$	5.91	-0.0001	-38.89	$3.9\cdot10^{-6}$	3.01	$8.8\cdot10^{-7}$	0.87	$-2.3\cdot10^{-5}$	-19.23
Relative cost of owning	-0.0005	-3.26	-0.0004	-2.67			-0.0003	-1.74	-0.0002	-1.34		
Location dummies (base-others)												
Isolated – countryside	0.2208	1.95	0.2294	2.07					0.0420	0.24		
Town outskirts	-0.3659	-4.47	-0.3526	-4.37					-0.3660	-3.01		
Between outskirts and city center	-0.3606	-4.39	-0.3312	-4.11					-0.3967	-3.29		
City center	-0.4840	-5.71	-0.4489	-5.38					-0.5692	-4.62		

City size (base < 500,000 inhab.)												
>500.000 inhab.	-0.3676	-6.60	-0.3456	-6.34					-0.3328	-4.88		
Credit constraints												
DCC (Direct answer from respondents)	-0.4970	-4.43	-0.4917	-4.49			-0.4963	-3.10	-0.4476	-3.27		
IC (Income constrained)	-0.3881	-5.93	-0.7887	-9.94								
WC (Wealth constrained)							-3.3366	-45.26	-4.0331	-51.64		
Outstanding bank debt dummies												
Purchase of real goods					-0.1362	-0.22					0.2077	0.63
Purchase of motor vehicles					-0.1321	-1.38					0.1401	2.35
Purchase of furniture, electrical appliances					0.2601	2.17					0.2290	2.88
Purchase of non-durable goods					0.2742	0.92					0.4807	2.96
ρ				0.4485						0.7874		
Wald test H_0:ρ=0				55.56						9.94		
Sample size							5,845					

Note: All the equations include year and regional dummies (20 regions).

Table 7: Estimates of the effect of labor income uncertainty on the probability of homeownership (bivariate probits with sample selection)

	Bivariate probit with sample selection						
	Coefficient	z-value	ρ	APE	Δp(y_{2i}=1) with 10% increase in $\hat{\sigma}^2_{\varepsilon i}$	Wald test H_0:ρ=0	Sample size
Income constrained (IC)							
IC=1	-0.8081	-6.09	0.0450	-0.2894	-2.95%	1.16	5,845
IC=0	-0.5976	-6.44		-0.2362	-2.41%	1.16	5,845
Wealth constrained (WC)							
WC=1	-0.1678	-1.55	-0.9827	-0.0669	-0.68%	1115.67	5,845
WC=0	-0.1968	-3.53		-0.0785	-0.80%	1115.67	5,845
Risk and non risk averse							
Risk averse=1	-0.8029	-4.70	0.0910	-0.319	-3.25%	7.89	2,944
Risk averse=0	-0.1041	-0.35		-0.041	-0.42%	7.89	2,944